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Using Wi-Fi Signals from Mobile Devices to Determine Characteristics of Pedestrian Behavior in Public Spaces

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ABSTRACT

This paper presents an investigation into automated data collection, applied to pedestrians in public spaces. Three case studies conducted in Brno, Czech Republic, a typical, medium-sized city in Central Europe, were used to determine the accuracy of the proposed method. Data was recorded in two ways: (i) automated data collection, using a data logger constructed on the principle of a minicomputer to measure the intensity of Wi-Fi signals from mobile devices and (ii) in situ observation. Data from in situ observation provided a basis for the comparison and verification of corresponding values from the automated data collection. The research framework of the paper comprises the determination of exact values for optimum characterization of pedestrian behavior in a given locality, taking into consideration conventions from previously published works: (i) the number of pedestrians N ; (ii) speed u ; (iii) flow q ; and (iv) density k . The results of this study confirm that as the density of the street network increases, the accuracy of the data collected by the digital method decreases significantly. These findings indicate that the method is more suitable for projects focused on identifying major trends or shifts in pedestrian preferences when navigating city centers than for projects that require exact counts in specific locations at a given time.

Keywords: Pedestrians, Speed, Density, Automatic Wi-Fi data collection.

INTRODUCTION

Quality of life in urban areas is an issue of great interest to the general public. More than half of the world's population currently live in urban areas, and urbanization is expected to increase in all regions of the world in the foreseeable future. By 2050, people living in cities and large urban agglomerations will make up nearly 70% of the global population (1). However, denser cities may threaten the quality of life of their inhabitants, including the use of public spaces. As European cities become increasingly crowded, the convenience of pedestrian movement has been significantly reduced. At the same time, walking has begun to attract attention as a key factor in establishing healthier, more ecological, and more socially active communities, and it is often the only effective form of transportation in city centers (2). Moreover, walking brings life to city streets, and pedestrians contribute to a safer urban environment, support increased accessibility, and promote the social integration of the population. In spite of this, cities have steadily become less pedestrian friendly over the last century (3).

Digital modelling can be a useful tool for maintaining sustainable living conditions in cities, and simulations of pedestrian movements can furnish operational information useful for strategic planning. For this reason, digital modelling has itself become the subject of scientific study. Data regarding pedestrian movement, numbers, and duration of stay form the basis of these models and can be obtained using techniques such as observation, questionnaires, and the monitoring of Wi-Fi signals, depending on the researchers' purpose and methods of analysis.

Existing research on variables relating to movement in urban spaces

Previous studies on pedestrian movement in public spaces have identified several important variables that characterize a given space, specifically: (i) speed u , (ii) flow q , (iii) density k , (iv) space y , (v) free-flow speed u_f , (vi) jam density k_j and their interrelationships (4). Studies involving pedestrian speed (5) and flow (6–8) have provided a number of dynamic models that were created based on both real measurements and simulations.

Traditionally, the basic relationship that has been used to describe pedestrian areas is that of flow and speed (4). Gradually, however, researchers have come to favor three more characteristic relationships (5): speed (u) and density (k); speed (u) and flow (q); and flow (q) and density (k).

There has already been a great deal of research into factors affecting pedestrian speed. Speed may be influenced by clothing style (9), age (10, 11), and gender (12) and is generally lower in developing countries (13). According to Zhou et al. (14), the effect of flow density on pedestrians with different walking speeds varies, with increasing density having the greatest negative impact on faster walkers (14). Rassaf and Mohajeri (15) found that adult women with a slower pace prefer to stay near commercial areas and shops. Adults, particularly men, prefer to use a longer stride and walk in the middle of the street, where their movement is not influenced by the shops along the sides of the street. Flow dynamics are also influenced by the distance between pedestrians (16). A comprehensive assessment of speed, density, and uniformity of pedestrian movement can help determine the probability of bottleneck forming (17).

Data acquisition and evaluation methods

Traditionally, studies of pedestrian behavior were based on in situ measurements (12); however, relying on direct observation for data acquisition often proves inadequate, owing to the sheer number of variables that need to be monitored simultaneously. Fieldwork in public spaces is by its very nature tiring and time-consuming (18). Also, when data is gathered by an observer, inaccuracies can occur (19). These shortcomings, combined with continuing technological advancement, have led researchers to explore other possibilities, such as studying mathematical and graphic relationships (20, 21), preparing questionnaires (2, 22, 23), and analyzing photographs and video recordings (17, 21, 24–26). Data from mobile operators can also be utilized, which has the advantage of automatic and continuous data transmission (27). This method is associated with considerable financial expense, however, and a large volume of data is best suited to extensive areas with high levels of pedestrian movement.

Another method of identifying pedestrian movement (28) and determining its direction (29) involves using Wi-Fi signals. Studies employing this method analyze wireless signals as they are reflected by different parts of the human body, detecting movement based on changes in signal amplitude and frequency. This method has limitations, however, that have thus far restricted its usefulness primarily to indoor areas. Because accuracy decreases as the number of subjects increases, this method is likewise unsuitable for areas where large numbers of people are present at the same time.

Nonetheless, there has been research into monitoring Wi-Fi signals outside of buildings. In a study by Traunmueller et al. (30), probe requests were collected from New York public access Wi-Fi networks in Manhattan. The research was made possible thanks to data acquired from access points (APs) located in public spaces. Accuracy was limited by the placement and density of the APs as well as by the need to correctly filter the acquired data so that the results would not be distorted by information from stationary devices. Another limiting factor was the inability of the researchers to precisely determine how many individuals in the area were unaccounted for.

Yet another study by Uras et al. (31) utilizes data from probe requests originating from equipment belonging to the research team, who placed their devices in three different locations in Italy. The study focused on the number of people in the given location, their positions, and how many times they returned to the location. The density of the crowd at each station was also calculated. Unfortunately, the results of this study were not validated by real-time observations of pedestrian behavior; therefore, it is impossible to say to what degree the results deviated from reality.

Data processing and evaluation is also possible using artificial neural networks (25, 32), automated analysis (33), a comparative approach (34, 35), and so on. Authors use various statistical approaches to data evaluation, one example being regression analysis, which is used to identify models capable of representing the phenomenon under study (36–39). Naturally, other types of statistical analyses are also used (24, 40, 41).

A review of the literature has shown that previous articles have focused on a wide range of monitoring methods, including the use of Wi-Fi signals. In contrast to other studies, the aim of this investigation was to field-test an affordable method of digital data collection by gathering probe requests with the help of a Wi-Fi signal receiver (data logger) of our own construction in order to offer a viable alternative for community-level research projects in urban spaces. This article presents the data obtained from the field tests and assesses the accuracy of this method, considering both the individual streets and the characteristics of pedestrian movement that were being monitored. At the same time, the idea of obtaining digital data without the necessity of being connected to public access Wi-Fi is further explored. The originality of this contribution lies in its attempt to determine the number and walking speed of pedestrians, their density, and flow by means of Wi-Fi signals from mobile devices moving past temporary checkpoints in the city center of Brno, Czech Republic.

METHODS

Two methods of data collection were used during this study: an observational method and an automated method. The automated method was chosen in order to test its effectiveness in a Central European context. Both methods allow for data on pedestrian movement to be determined in accordance with the methodology formulated by the Gehl Institute (42):

- number of pedestrians (N_p) passing through the area being monitored.
- median walking speed (u), derived from the number of pedestrians passing through the area within a unit of time.

Further characteristics of pedestrian movement as defined by Daamen were also determined (5):

- flow (q), which is defined as the sum of the distances covered by pedestrians moving in one direction in the area being studied in a given period of time. **Equation 1:**

$$qx = \frac{\sum_{i \in C} Di}{XYT} \text{ and } qy = \frac{\sum_{i \in C} Zi}{XYT} \quad (1)$$

where

- Di is the distance covered by the i -th pedestrian in direction x ,
- Zi is the distance covered by the i -th pedestrian in direction y ,
- XY is the area of the street being studied, and
- T is the walking time in which the i -th pedestrian moves through the area being studied, which is defined as $X \times Y \times T$, and

- density (k), which is defined as the ratio of the number of pedestrians to the area being studied.

Equation 2:

$$k = \frac{N_e}{XY} \quad (2)$$

where

N_e is the number of entities, obtained from the data loggers, and
 XY is the area being studied.

Both methods of data collection were used concurrently in each location during two time periods per day.

Conditions

Owing to the social dimension of this research and because our intent was to evaluate the quality of the urban space according to whether it encouraged walking, we chose 1–2 p.m. and 4–5 p.m. on weekdays as the observation times for data collection. Measurements were taken under the following conditions: sunny weather and a temperature around 20 °C (19). Calibration was carried out in May 2019, and the main data collection took place in August 2019. Measurements for both methods (observational and automated) were taken concurrently in the section of the street being studied in order to evaluate the accuracy of the automated method.

The observational method

For the observational data collection method, three observers were stationed at each location, one near the central data logger and the others at the entrances to the section. The observers at the entrances were tasked with counting the total number of pedestrians passing down the entire length of the section, demarcated by a "virtual fence." Measurements were taken at each entrance once per hour during a fifteen-minute interval and subsequently multiplied by four. The median walking speed was recorded by the centrally located observer, who used a stopwatch to measure how long it took for a sample of 15 pedestrians to traverse the entire length of the section in both directions (meaning a total of 30 pedestrians were recorded each hour). The values in the text are the median walking speed.

The automated method

For the automated data collection method, the number of pedestrians corresponds to the number of mobile devices transmitting a Wi-Fi signal in the section of the street being monitored. A prototype of a minicomputer with a Wi-Fi receiver (i.e., a data logger), specially designed for field measurements, was used to capture these signals (43). Three data loggers were temporarily placed in the chosen location, one in the center (DLC) and one at either end (DLO-1, DLO-2). Entities were counted continuously during each of the one-hour intervals. The median walking speed was calculated based on the passage times measured between checkpoints.

The data logger

In terms of hardware, the data logger functions as a network of receivers capable of capturing the signal transmitted by mobile devices searching for Wi-Fi hotspots. It comprises several basic components:

- Orange Pi – a minicomputer
- A Wi-Fi receiver, in monitor mode, that receives signals from mobile phones and devices with the Wi-Fi modem switched on within a 150-meter radius, depending on the surroundings. Signal strength ranges within negative dBm. Near the data logger, measured values approach zero, falling as the distance from the device increases. The signal is lost above approximately -100 dBm when the mobile device moves outside the radius of the data logger.
- A memory card
- An external battery [20,000 mAh], sufficient for sixteen hours of measurement
- A real-time clock module with a battery backup

- A passive cooling system to prevent overheating. The device has an activation temperature of 50 °C and a regular operating temperature of 65 °C while 80 °C is critical. A drop in the power supply can result in data logger or Wi-Fi adapter failure.
- A display showing current data.

Software

The prototype uses an ARMBIAN operating system (44). When reading data from Wi-Fi devices, it uses WIRESHARK software for network communication analysis (45) or the terminal version, TSHARK. This software can be set up to switch the Wi-Fi adapter to monitor mode, thereby recording information from mobile devices in the proximity of the data logger.

Configuration

After being connected to a power source, the data logger is programmed to launch scripts in the languages BASH (46) and PYTHON (47) that initiate signal reception from Wi-Fi-enabled devices in the surrounding area and record signal strength. Other scripts check the condition of the device, display operational information on the attached LCD screen module, and restart the device if an error that interrupts the data acquisition process occurs. Information is stored in CSV format and contains the time, length of connection, ID of the anonymized device, and signal strength.

Before data collection could commence, it was necessary to perform a calibration of the triad of data loggers, taking into consideration the varying configurations of the selected streets. First, the data logger operator, functioning as a mock pedestrian, walked the perimeter of the area under study while carrying a Wi-Fi-enabled mobile phone. As the data logger captured the probe requests of this test phone, it used their signal strength to demarcate a so-called "virtual fence" around the area. Signal strength values at each data logger also provided the basis from which the limit values and reference placement of the data loggers were set. These signal strengths were subsequently displayed on thematic maps using GIS. Once set, the limit values for signal strength along the "virtual fence" allowed data to be filtered so that entities outside the area were excluded from the results.

The data loggers were arranged in the following manner: one was placed at each entrance to the area being studied as a checkpoint and was marked on the map as DLO-1 and DLO-2. The main data logger, DLC, was placed in the center of the area to record the entire set of entities, using the unique MAC addresses of the mobile devices. This information was subsequently anonymized to protect the privacy of those involved. As entities passed through the area, their mobile devices were continually searching for and connecting to the data logger with the strongest signal (i.e., the closest device). In order to follow this passage, the threshold value of the signal strength at which the mobile devices switched their connection preference from the entry checkpoints, DLO-1 and DLO-2, to the central data logger, DLC, was also determined.

Processing the data

The movement of entities in the section of the street circumscribed by the "virtual fence" was recorded to a database, and the records were subsequently filtered by means of program scripts.

Filtering took place in the following three steps:

1. The removal of entities that are not pedestrians but whose signal encroaches on the area inside the "virtual fence" (e.g., mobile devices located in passing vehicles or surrounding buildings). Entities were filtered out if the length of time they spent in the area was less than 10 seconds or more than 45 minutes. This filtration process proceeded in the same way for all three sites.
2. The removal of entities that transmitted a signal to only one checkpoint (DLC, DLO-1, or DLO-2). Entities were retained if they transmitted a signal to DLC and were also recorded by DLO-1 or DLO-2. Minimum signal strength was determined independently for each of the sites being investigated using standard calibration (**Figure 1**). Consequently, the resulting number of entities (N_{e1}) corresponds to the number of Wi-Fi-enabled mobile phones whose signals were received by DLC and at least one other data logger. (See **Table 1**)
3. Entities (N_{e2}) whose signals were captured only by DLC but whose signal strength was comparable to values measured during calibration near the boundaries of the area were included in the

calculations for passage time. In **Table 2**, the median length of time required to pass through the area around DLC is given for individual streets.

[insert Figure 1.]

Selecting the sites for the case studies

Three streets in the historical city center of Brno, a South Moravian metropolis (approximate population–380,000), were chosen to test the validity of using Wi-Fi signals from pedestrians' mobile devices for the purposes of data acquisition in a European context. The streets, Česká Street, Panská Street and Minoritská Street, have a number of similarities: length: 75–110 m, width of the street profile: 8–13 m, area: 780–1,200 m², gradient: 0.9–5.5%, height of surrounding development: 2–6 stories (**Figure 2**).

[insert Figure 2.]

Česká Street

Česká Street links the public transport hub Joštova/Česká with the square Náměstí Svobody in the center of the city, giving this area the character of a thoroughfare. The length of the section selected for study is 75 m. The width ranges from 8 to 13 m, and the area of the section is 780 m². The average gradient is 2.6%. The street is lined by development between 3 and 6 stories high. Adjacent streets are fairly quiet with little pedestrian traffic.

Panská Street

Panská Street lies on a route connecting Zelný Trh, a popular gastronomic destination with a bustling farmers' market, and Náměstí Svobody, a centrally located square. Furthermore, its western end links up with a route that leads toward a public transport hub with connections to both the main railway station and "Old Brno," a sort of gateway to the historical center. The length of the section is 110 m. The width ranges from 8 to 12 m. The area is 1,200 m², and the average gradient is 5.5%. The street is lined with development between 3 and 5 stories high and takes on the character of a thoroughfare in the direction of Zelný Trh. Panská Street lies on a tourist route thanks to its proximity to a nearby network of highly frequented public spaces.

Minoritská Street

Minoritská Street is the quietest of the three locations and does not link any important squares; however, it is located on the route connecting the main railway station transit center and the transport hub Joštova/Česká. The length of the section is 110 m. The width ranges from 8 to 12 m. The area is 1,058 m², and the average gradient is 0.9%. The street is lined by development ranging from 2 to 6 stories in height. Streets in the adjacent area are similarly frequented.

RESULTS

The acquired data can be divided into two categories according to its purpose:

- Data from calibration – used for analyses of Wi-Fi signal propagation in the section of the street being studied.
- Data from the main data collection – used to calculate the characteristics of pedestrian behavior described in the Methods section as well as to evaluate the accuracy of the automated method as opposed to traditional observational methods.

Standard calibration

A "virtual fence" was erected at each location (as described in the section entitled "Configuration.") The signal strength within this "fence" ranged between -65 and -85 dBm. Only entities whose transmissions fell within these limits were recorded in the database.

[insert Figure 3.]

The values measured during calibration were recorded on maps, one for each of the locations in this study. The following information is for Minoritská Street (**Figure 3**). For the data logger positioned at the northern

edge of the area (DLO-1), the threshold value was -75 dBm. The central data logger (DLC) registered a value of -87 dBm at the edges of the "virtual fence" in the direction of the entry checkpoints. The threshold value for the data logger at the southern edge of the section (DLO-2) was -85 dBm.

[insert Figure 4.]

For Panská Street (**Figure 4**), the data logger positioned at the western edge of the area (DLO-1) registered a threshold value of -85 dBm. The central data logger (DLC) registered a value of -77 dBm at the edges of the "virtual fence" in the direction of the entry checkpoints. The threshold value for the data logger at the eastern edge (DLO-2) was -73 dBm.

[insert Figure 5.]

For Česká Street (**Figure 5**), the data logger positioned at the northern edge of the area (DLO-1) registered a threshold value of -82 dBm. The central data logger (DLC) registered a value of -84 dBm at the edges of the "virtual fence" in the direction of the entry checkpoints. The threshold value for the data logger at the southern edge (DLO-2) was -85 dBm.

The limit values for the recorded strength of the Wi-Fi signal of the entities being monitored (presented in **Table 1**) were stipulated for the purposes of data filtration with a view to excluding mobile devices outside the boundaries of the area being studied, e.g., those in nearby streets. At the same time, entities whose signal strength fell within these limit values were subjected to an additional verification process, which confirmed a probe request having been sent from the entity to the DLC and at least one other data logger. Limit values (in dBm) can be summarized as follows: for Minoritská Street, -75 for DLO-1, -85 for DLC, and -85 for DLO-2; for Panská Street, -80 for DLO-1, -75 for DLC and -70 for DLO-2; for Česká Street, -85 for DLO-1, -80 for DLC and -85 for DLO-2.

Resultant values for investigated characteristics

Pedestrian numbers, flow, and density

During the fieldwork portion of this study, a total number of pedestrians was recorded by in situ observers and a total number of entities was recorded by the data loggers. The greatest number of pedestrians (2,526) was found on Česká Street between 4 and 5 p.m. In the same time frame, data loggers on this street recorded 10,162 unique entries. After filtering out entities whose signal strength lay outside the limits defined during calibration, 6,860 entries remained. The next level of filtration removed entities that did not meet the requirement of having connected to at least two data loggers, leaving 1,701 entries. During the final filtration, entities that had failed to connect to the central data logger as well as to one of the data loggers positioned near an entry checkpoint were eliminated. A total of 1,180 entries (N_{e1}) survived the entire filtration process, meaning that the automated method recorded 1,346 fewer pedestrians or just 47% of the total number recorded by the observational method. (See **Table 1**) The least number of pedestrians (829) was observed on Panská Street between 1 and 2 p.m. At the same time, 112 entities, filtered from a total of 8,777 entries, were detected by the data loggers. This is 717 fewer pedestrians or approximately 14% of the total number found by observation.

The highest flow of pedestrians (q_p) as calculated from observational data, 8.5 N_{p1}/ms ; 9.5 N_{p1}/ms , was found on Česká Street; however, the flow of entities (q_e) as calculated from digital data amounted to 4.4 N_{e1}/ms ; 4.1 N_{e1}/ms , which corresponds to 52% of the number of pedestrians from 1 to 2 p.m. and 43% of the number of pedestrians from 4 to 5 p.m. The lowest value for the flow of pedestrians was found on Panská Street from 1 to 2 p.m. at 1.1 N_{p1}/ms , whereas the value for the flow of entities was 0.2 N_{e1}/ms , which is 82% (0.9 N/ms) lower.

The highest density of pedestrians (k_p), 3.2 N_{p1}/m^2 , was found on Česká Street from 4 to 5 p.m. and the lowest, 0.7 N_{p1}/m^2 , was found on Panská Street from 1 to 2 p.m. The density of entities (k_e) on Česká Street from 4 to 5 p.m. was determined to be 47% of the value of k_p , which is 1.7 N/m^2 less. The lowest density of entities, 0.1 N_{e1}/m^2 , was found on Panská Street from 1 to 2 p.m., which corresponds to 14% of the value of k_p (0.6 N/m^2 less).

TABLE 1 A comparison of values for the median number of pedestrians/entities

Streets	Observational data			Digital data			
	N_{p1}	q_p (N_{p1}/ms)	k_p (N_{p1}/m^2)	N_{e1}	N_{e1}/N_p (%)	q_e (N_{e1}/ms)	k_e (N_{e1}/m^2)
Minoritská Street							
1–2 p.m.	1,178	1.7	1.1	713	61	1.6	0.7
4–5 p.m.	1,918	2.8	1.8	-	-	-	-
Panská Street							
1–2 p.m.	829	1.1	0.7	112	14	0.2	0.1
4–5 p.m.	864	1.1	0.7	163	19	0.3	0.1
Česká Street							
1–2 p.m.	2,217	8.5	2.9	1,333	61	4,4	1.7
4–5 p.m.	2,526	9.5	3.2	1,180	47	4,1	1.5

N_{p1} = pedestrian number

q_p = pedestrian flow

k_p = pedestrian density

N_{e1} = entity number

q_e = entity flow

k_e = entity density

Average walking speed

A combination of in situ observation and recordings from data loggers furnished the information on the walking speed, based on the median passage time of pedestrians/entities. For the 110-meter-long section of Minoritská Street, data collected by observers between 1 and 2 p.m. yielded a walking speed (u_p) of 1.5 m/s while data loggers recorded a walking speed (u_e) of 1.6 m/s. During the second observation period (4–5 p.m.), observers found the walking speed (u_p) to be 1.5 m/s. Unfortunately, due to a failure of the central data logger, the data for entities was not stored during this period.

For the 110-meter-long section of Panská Street, data collected by observers between 1 and 2 p.m. yielded a walking speed (u_p) of 1.6 m/s while data loggers recorded a walking speed (u_e) of 2.9 m/s. During the second observation period (4–5 p.m.), observers found the walking speed (u_p) to be 1.5 m/s. The walking speed (u_e) recorded by data loggers was 1.6 m/s.

For the 75-meter-long section of Česká Street, data collected by observers between 1 and 2 p.m. yielded a walking speed (u_p) of 2.0 m/s while data loggers recorded a walking speed (u_e) of 1.3 m/s. During the second observation period (4–5 p.m.), observers found the walking speed (u_p) to be 2.0 m/s. The walking speed (u_e) recorded by data loggers was 0.7 m/s. (See **Table 2.**)

TABLE 2 A comparison of values for the median walking speed of pedestrians/entities

Streets	Observational data			Digital data		
	N_{p2}	travel time (s)	u_p (m/s)	N_{e2}	travel time (s)	u_e (m/s)
Minoritská Street						
1–2 p.m.	30	73	1.5	103	69	1.6
4–5 p.m.	30	72	1.5			-
Panská Street						
1–2 p.m.	30	70	1.6	18	38	2.9
4–5 p.m.	30	72	1.5	7	67	1.6
Česká Street						
1–2 p.m.	30	37	2.0	117	60	1.3

4–5 p.m.	30	38	2.0	57	101	0.7
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N_{p2} = pedestrian number

u_p = pedestrian speed

N_{e2} = entity number

u_e = entity speed

DISCUSSION

When evaluating the results of this study, the most obvious issue that needs to be addressed is the low/variable accuracy of the data obtained by automated means compared to that compiled by in situ observers. An analysis of the data shows that on longer, continuous street segments, such as those found on Česká and Minoritská Streets, regardless of the amount of pedestrian traffic, the number of entities identified using the automated method reaches an accuracy of roughly 50%, but on the section lying within a more complex street network (Panská), the accuracy falls to nearly 20%. One explanation for this variation could be a shorter overall duration of stay, with entities leaving the monitored area by way of Radnická Street, which merges with Panská near the midpoint of the section.

Several other factors may have influenced overall accuracy, one being signal deviation. Wi-Fi signals in public spaces can be affected by interference often due to a discharge in tram trolleys or the presence of a water reservoir, but even the presence of other people can interfere with a Wi-Fi signal since water comprises a large proportion of the human body.

Yet another consideration appears in the work of Julien Freudiger (48), who investigated in detail the behavior of mobile devices in an environment with more than one accessible Wi-Fi network. He determined eight separate factors influencing the frequency of probe requests from individual devices, and the complexity of this issue as it is depicted in his work leads to the conclusion that there is little that can be done to influence this facet of the problem when observing pedestrians in public spaces.

In our investigation, short street sections and long intervals between probe requests from some mobile devices meant that there were devices that did not have time to connect to two data loggers as the entity traversed the section and were subsequently filtered out of the database, decreasing the total number of recorded entities. A solution for this particular difficulty could be the placement of another data logger outside the virtual fence, either on the same or a neighboring street.

The relationship between speed, density and flow, defined by Daamen and Chen (5, 6), was not demonstrated to any significant degree by the case study in Brno. This is probably due not only to the limited number of entities recorded but also to inaccuracies in the duration of stay as recorded by the data loggers, which adversely affected the calculation of speed and flow.

The walking speed of entities differs significantly among the three locations. For the observation method, the number of pedestrians chosen for timing was fixed at 30 per hour. Any pedestrian entering a building was eliminated from the sample. As a rule, no one lingered inside the "virtual fence." For the automated method, calculations made use of the median passage time around DLC, which balanced out extremes (someone running through the area or stopping for an extended period of time). Nevertheless, in every location the median passage time recorded by the data loggers was higher than the values measured during observation, with the exception of Panská Street, where the street network is denser. There, values dropped by half. It is also necessary to note that having a mobile device may in itself slow the speed of an entity (when making calls, for example).

CONCLUSIONS

This study was designed to validate the actual applications of a particular method of automated data acquisition under field conditions while identifying factors that might adversely affect the accuracy of the method, especially limits imposed by the current level of technology. When comparing the automated method to in situ observation, the automated method demonstrated up to 50% accuracy, which significantly affects subsequent calculations made using this data. Even though the chosen method did not demonstrate sufficient accuracy for following absolute numbers of pedestrians/entities, it shows promise for monitoring relative numbers, which can be used to follow mobility patterns and utilization trends in urban areas, an example being the routes most frequently chosen for navigating the city center. Similar technology was used for data acquisition to predict trends in pedestrian populations in Lower Manhattan in 2017 (30).

The shortcomings and limitations uncovered in this case study and revealed in the literature review should not be taken as justification for abandoning research in this area. As technological advancement continues, it may soon be possible to protect user privacy while allowing researchers access to the more stable telephone signal rather than the difficult to capture Wi-Fi signal, or there may be advancement in Wi-Fi signal detection. Whatever the case, more effort needs to be spent on finding research applications that take advantage of those qualities that make this kind of automated data acquisition so attractive (especially for small-scale, local projects with limited resources): accessibility, affordability, easy operation and programmability of the device, and open source software. These same characteristics allow cities and universities to partner with commercial businesses in developing this technology as communities work together to create urban spaces that are safe, accessible, and wholesome for generations yet to come.

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AUTHOR CONTRIBUTION

The authors confirm contribution to the paper as follows: study conception and design: E. Šimara, P. Kilnarová, R. Vašut; data collection: E. Šimara, P. Kilnarová, R. Vašut; analysis and interpretation of results: E. Šimara, P. Kilnarová, J. Palacký; draft manuscript preparation: E. Šimara, P. Kilnarová, J. Palacký. All authors reviewed the results and approved the final version of the manuscript.

CONFLICT OF INTEREST

The authors do not have any conflicts of interest to declare.

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Figure Legend:

Figure 1 Secondary filtration – diagram of signal strength

Figure 2 The location of the case studies on a map of the historical city center

Figure 3 Signal strength values at the boundaries of the selected area on Minoritská Street

Figure 4 Signal strength values at the boundaries of the selected area on Panská Street

Figure 5 Signal strength values at the boundaries of the selected area on Česká Street